

# Online machine learning with decision trees

---

Max Halford

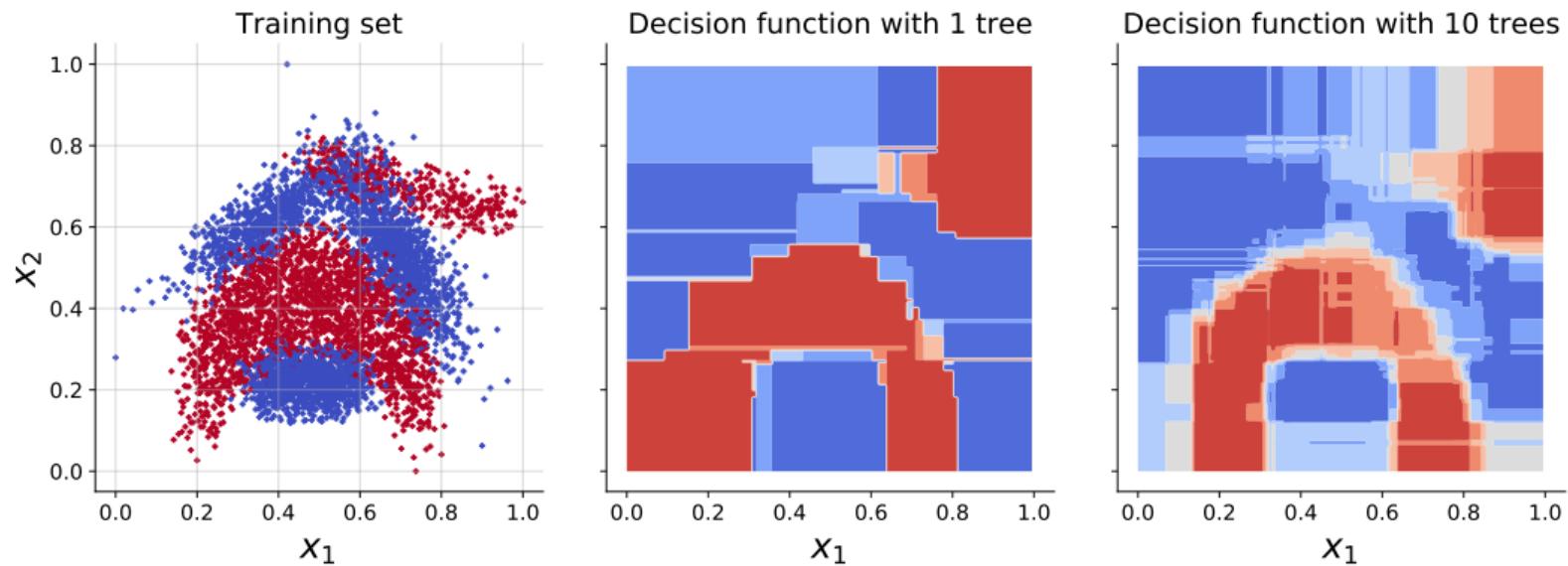
University of Toulouse  
Thursday 7<sup>th</sup> May, 2020

# Decision trees

- “*Most successful general-purpose algorithm in modern times.*” [HB12]
- Sub-divide a feature space into partitions
- Non-parametric and robust to noise
- Allow both numeric and categorical features
- Can be regularised in different ways
- Good weak learners for bagging and boosting [Bre96]
- See [BS16] for a modern review
- Many popular open-source implementations [PVG<sup>+</sup>11, CG16, KMF<sup>+</sup>17, PGV<sup>+</sup>18]

Alas, they assume that the data can be scanned more than once, and thus can't be used in an online context.

# Toy example: the banana dataset<sup>1</sup>



<sup>1</sup>[Banana dataset on OpenML](#)

# Online (supervised) machine learning

- Model learns from samples  $(x, y) \in \mathbb{R}^{n \times p} \times \mathbb{R}^{n \times k}$  which arrive in sequence
- Online != out-of-core:
  - Online: samples are only seen once
  - Out-of-core: samples can be revisited
- **Progressive validation [BKL99]:**  $\hat{y}$  can be obtained right before  $y$  is shown to the model, allowing the training set to also act as a validation set. No need for cross-validation!
- Ideally, **concept drift** [[GŽB<sup>+</sup>14](#)] should be taken into account:
  1. **Virtual drift:**  $P(X)$  changes
  2. **Real drift:**  $P(Y | X)$  changes:
    - ▶ Example: many 0s with sporadic bursts of 1s
    - ▶ Example: a feature's importance changes through time

# Online decision trees

- A decision tree involves enumerating split candidates
- Each split is evaluated by scanning the data
- This can't be done online without storing data
- Two approaches to circumvent this:
  1. Store and update feature distributions
  2. Build the trees without looking at the data (!!)
- Bagging and boosting can be done online [OR01]

# Consistency

- Trees fall under the non-parametric regression framework
- Goal: estimate a regression function  $f(x) = \mathbb{E}(Y | X = x)$
- We estimate  $f$  with an approximation  $f_n$  trained with  $n$  samples
- $f_n$  is consistent if  $\mathbb{E}(f_n(X) - f(X))^2 \rightarrow 0$  as  $n \rightarrow +\infty$
- Ideally, we also want our estimator to be unbiased
- We also want regularisation mechanisms in order to generalise
- Somewhat orthogonal to concept drift handling

# Hoeffding trees

- Split thresholds  $t$  are chosen by minimising an impurity criterion
- The impurity looks at the distribution of  $Y$  in each child
- An impurity criterion depends on  $P(Y | X < t)$
- $P(Y | X < t)$  can be obtained via Bayes' rule:

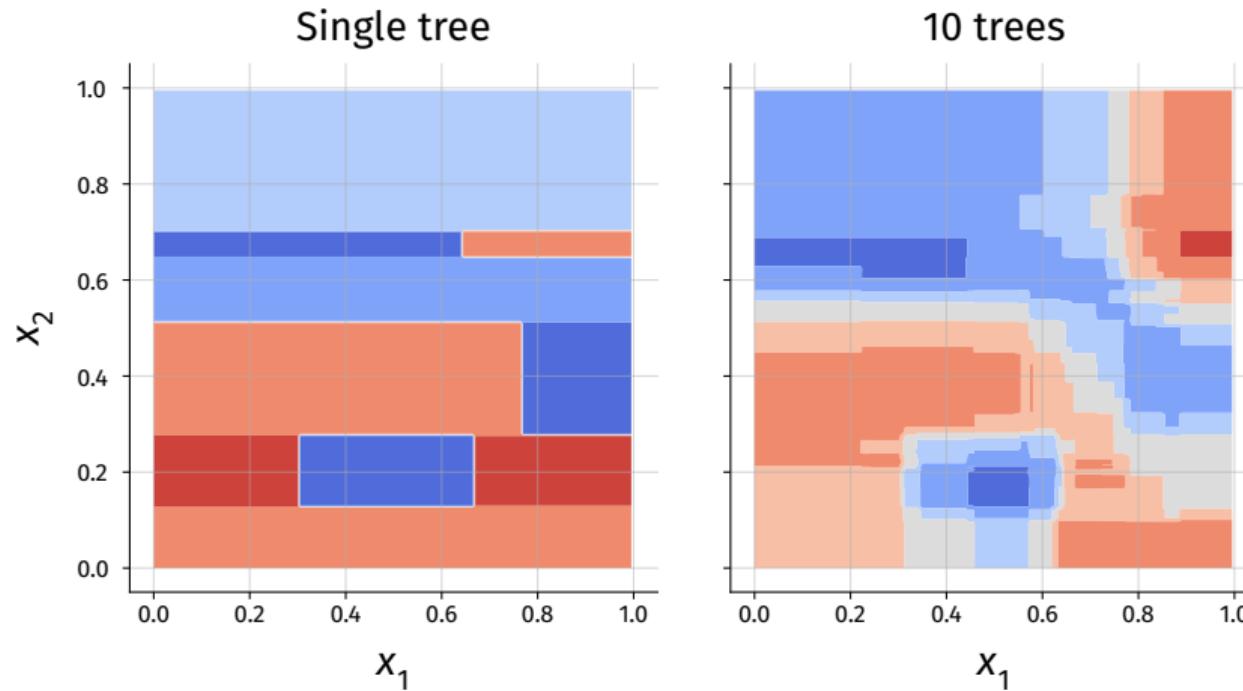
$$P(Y | X < t) = \frac{P(X < t | Y) \times P(Y)}{P(X < t)}$$

- For classification, assuming  $X$  is numeric:
  - $P(Y)$  is a counter
  - $P(X < t)$  can be represented with a histogram
  - $P(X < t | Y)$  can be represented with one histogram per class

# Hoeffding tree construction algorithm

- A Hoeffding tree starts off as a leaf
- $P(Y)$ ,  $P(X < t)$ , and  $P(X < t | Y)$  are updated every time a sample arrives
- Every so often, we enumerate some candidate splits and evaluate them
- The best split is chosen if significantly better than the second best split
- Significance is determined by the Hoeffding bound
- Once a split is chosen, the leaf becomes a branch and the same steps occur within each child
- Introduced in [DH00]
- Many variants, including revisiting split decisions when drift occurs [HSD01]

# Hoeffding trees on the banana dataset



# Mondrian trees

- Construction follows a Mondrian process [RT<sup>+</sup>08]
- Split features and points are chosen without considering their predictive power
- Hierarchical averaging is used to smooth leaf values
- First introduced in [LRT14]
- Improved in [MGS19]

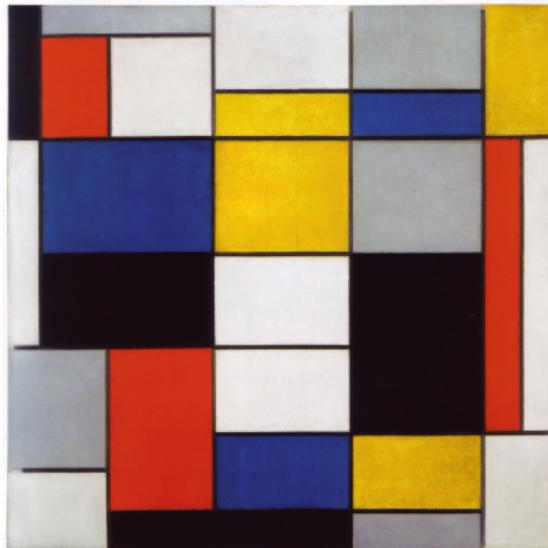
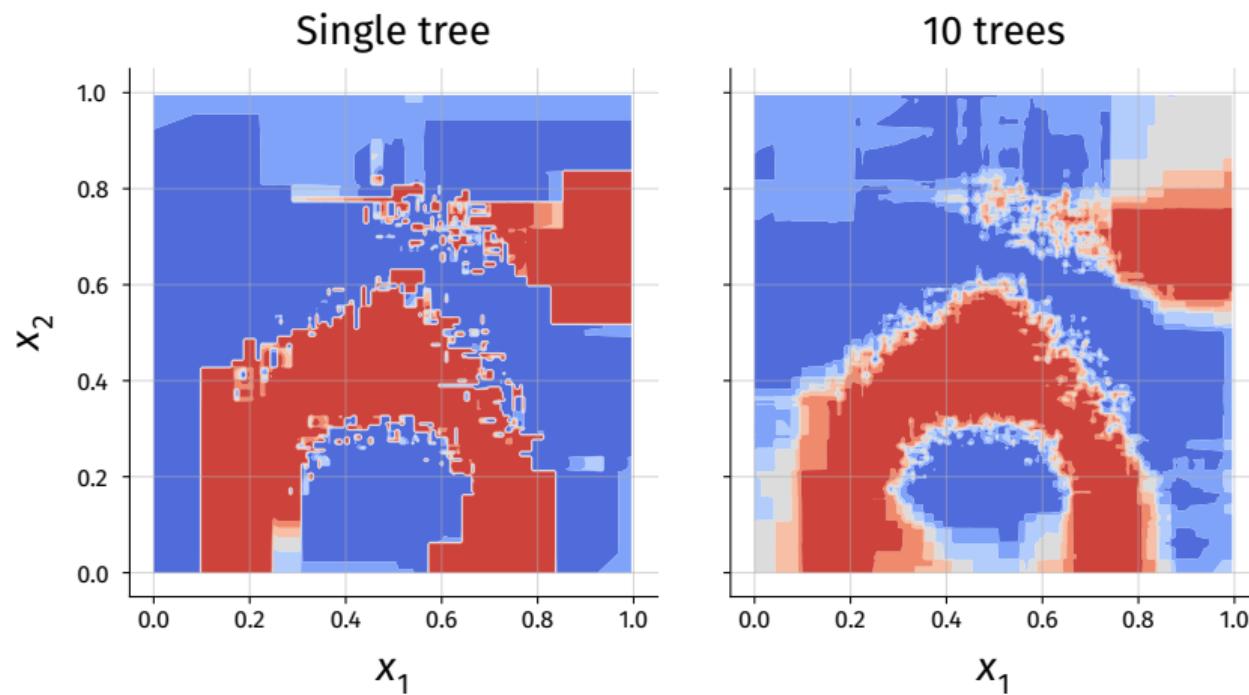


Figure: *Composition A* by Piet Mondrian

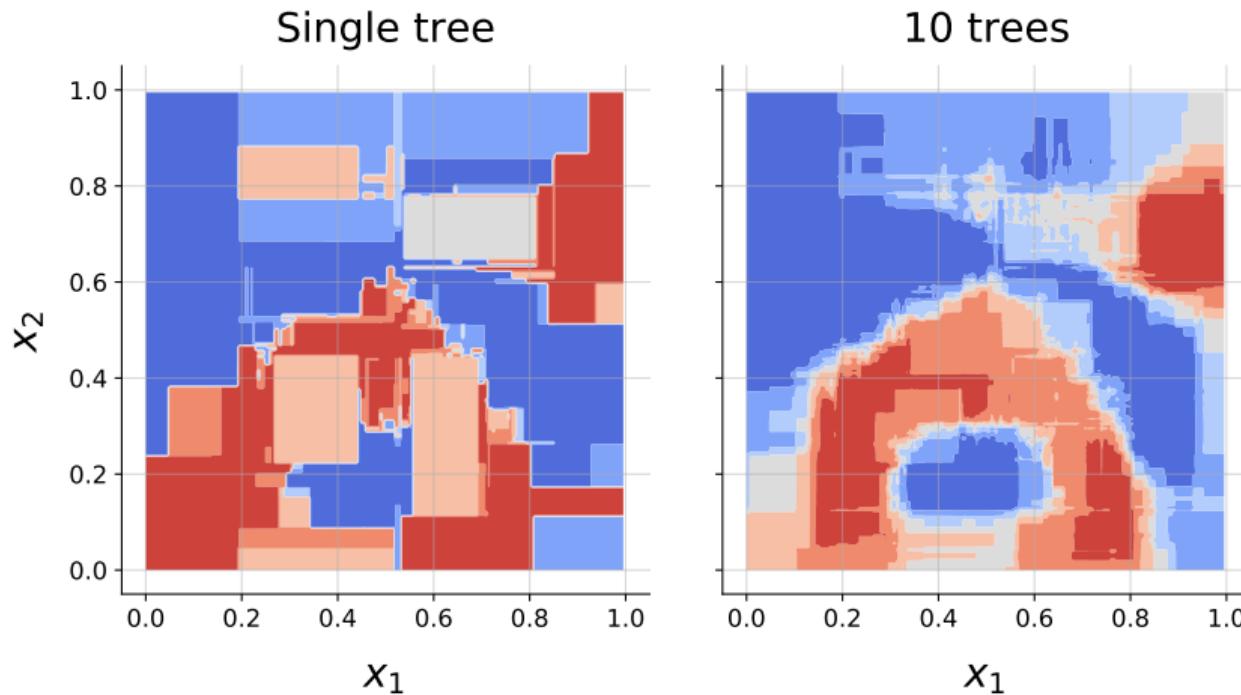
# The Mondrian process

- Let  $u_j$  and  $l_j$  be the bounds of feature  $j$  in a cell
- Sample  $\delta \sim \exp(\sum_{j=1}^p u_j - l_j)$
- Split if  $\delta < \lambda$
- The chances of splitting decrease with the size of the cells
- $\lambda$  is a soft maximum depth parameter
- Features are uniformly chosen in proportion to  $u_j - l_j$
- More information in [these slides](#)

# Mondrian trees on the banana dataset



# Aggregated Mondrian trees on the banana dataset



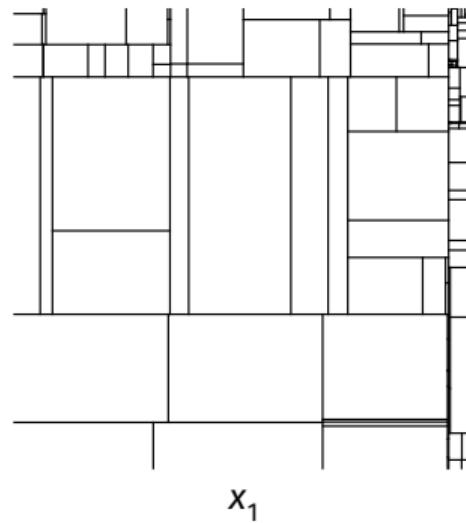
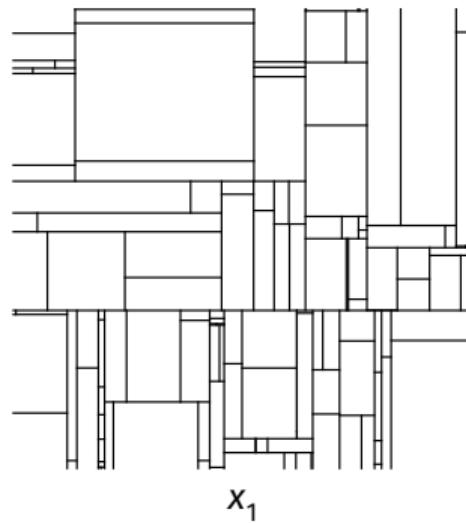
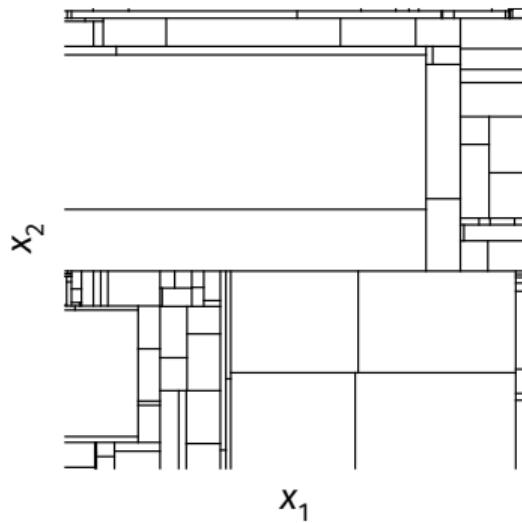
# Purely random trees

- Features  $x$  are assumed to be in  $[0, 1]^p$
- Trees are constructed independently from the data, before it even arrives:
  1. Pick a feature at random
  2. Pick a split point at random
  3. Repeat until desired depth is reached
- When a sample reaches a leaf, said leaf's running average is updated
- Easier to analyse because tree structure doesn't depend on  $Y$
- Consistency depends on:
  1. The height of a tree – denoted  $h$
  2. The amount of features that are “relevant”

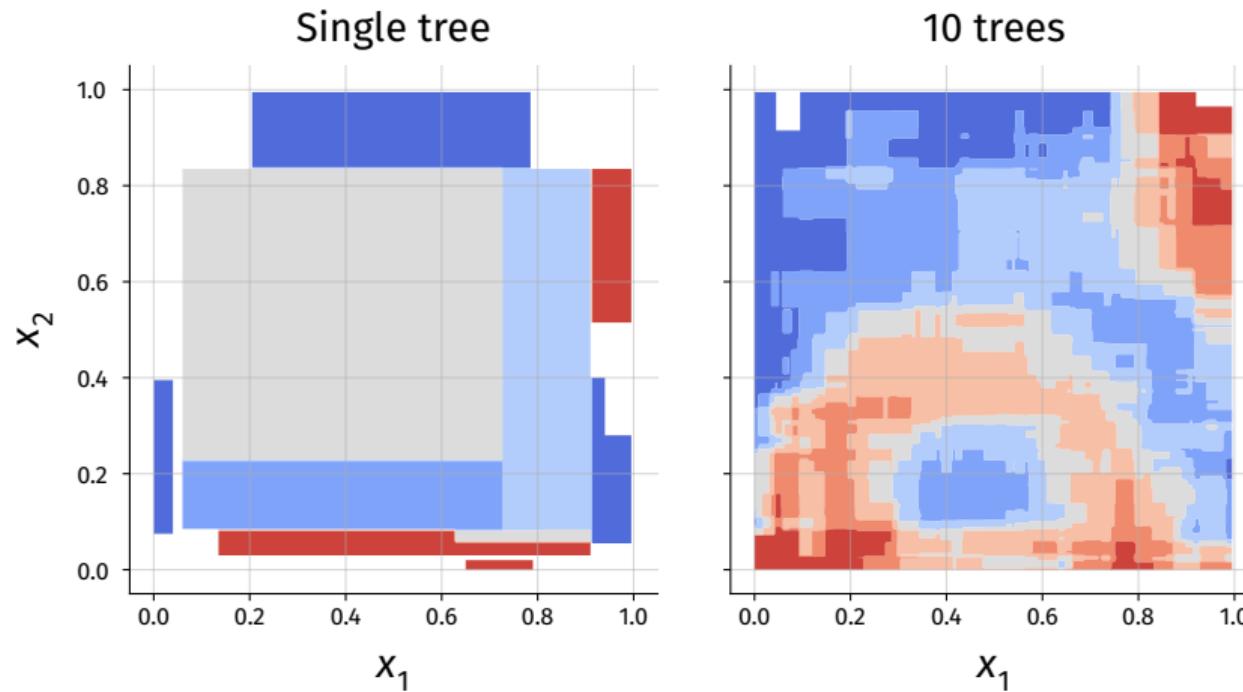
# Uniform random trees

- Features and split points are chosen completely at random
- Let  $h$  be the height of the tree
- Consistent when  $h \rightarrow +\infty$  and  $\frac{h}{n} \rightarrow 0$  as  $h \rightarrow +\infty$  [BDL08]

# Uniform random trees



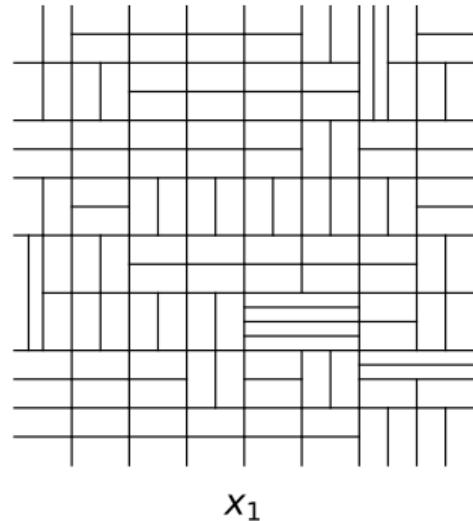
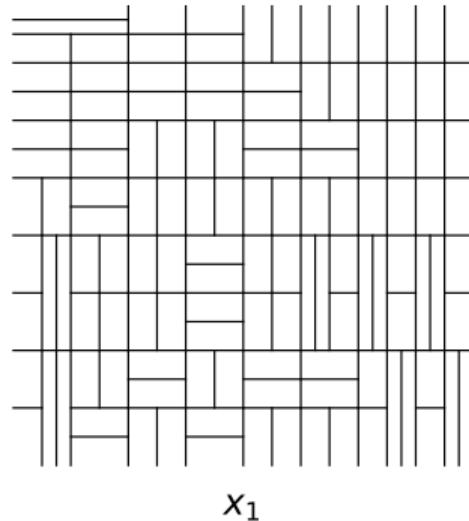
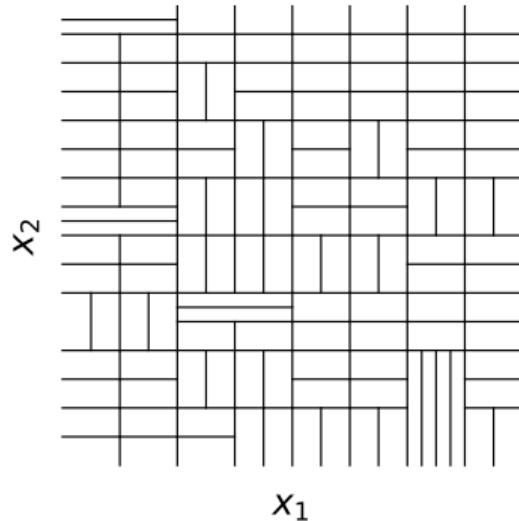
# Uniform random trees on the banana dataset



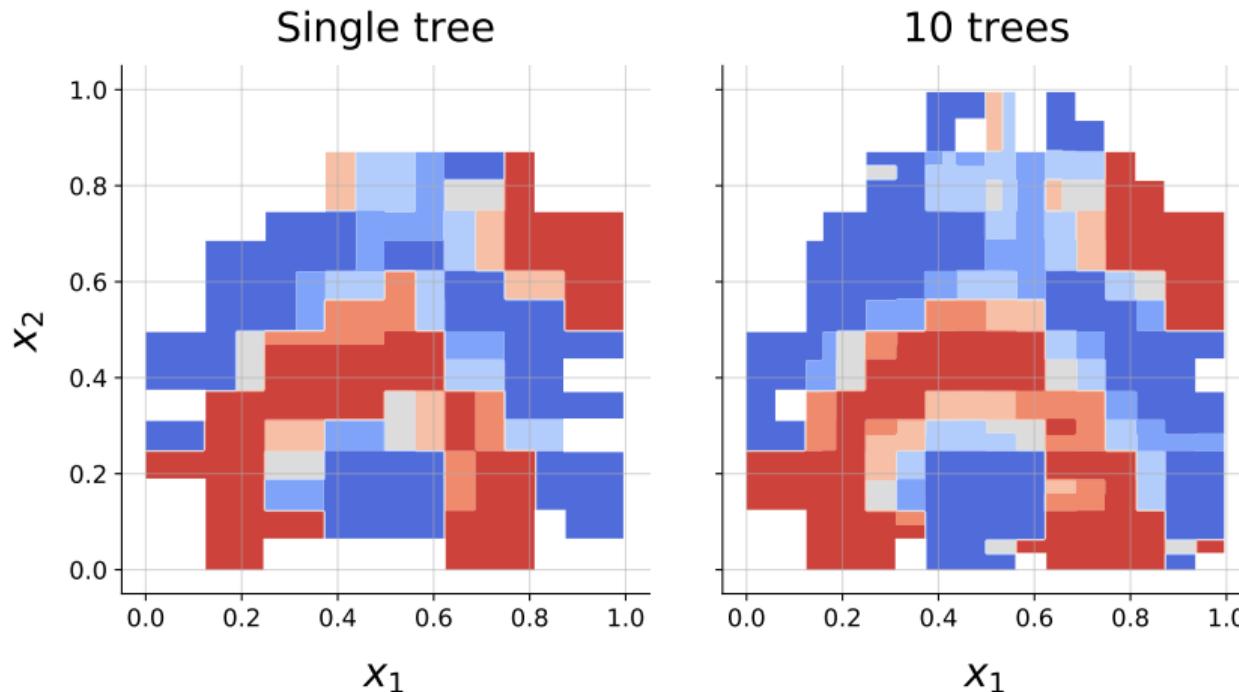
# Centered random trees

- Features are chosen completely at random
- Split points are the mid-points of a feature's current range
- Consistent when  $h \rightarrow +\infty$  and  $\frac{n}{2^h} \rightarrow 0$  as  $h \rightarrow +\infty$  [Sco16]

# Centered random trees

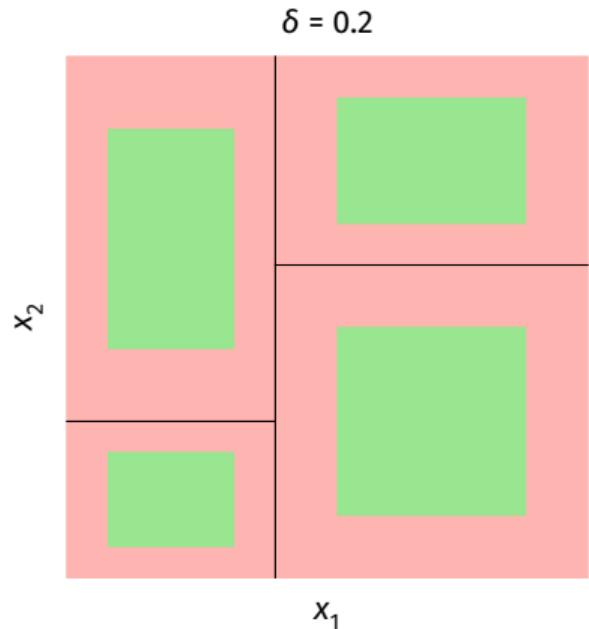


# Centered random trees on the banana dataset

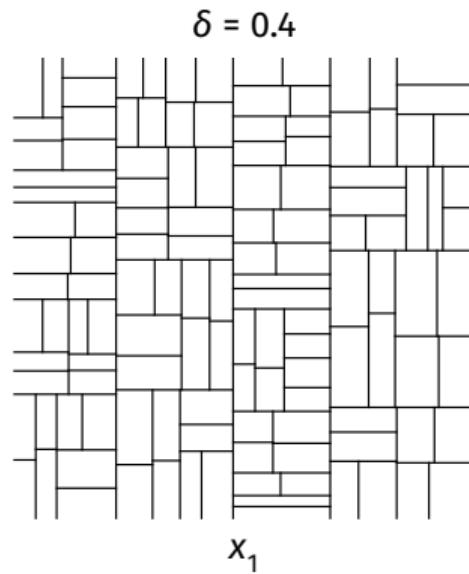
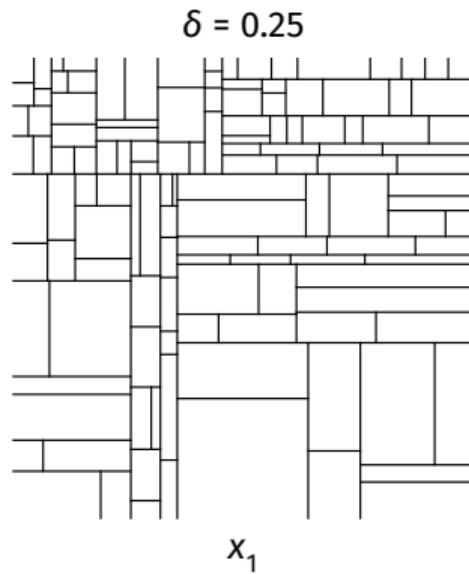
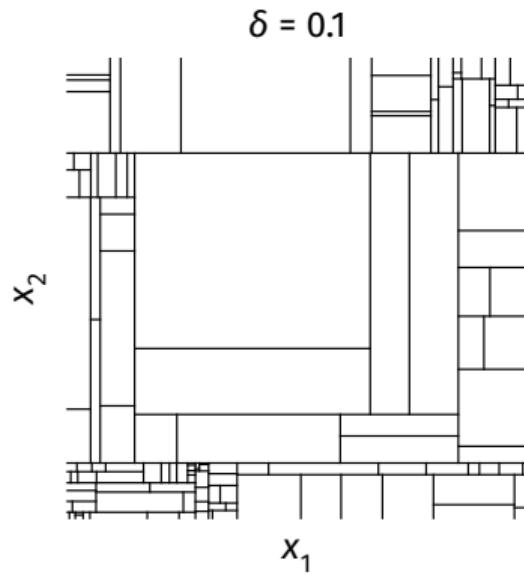


# How about a compromise?

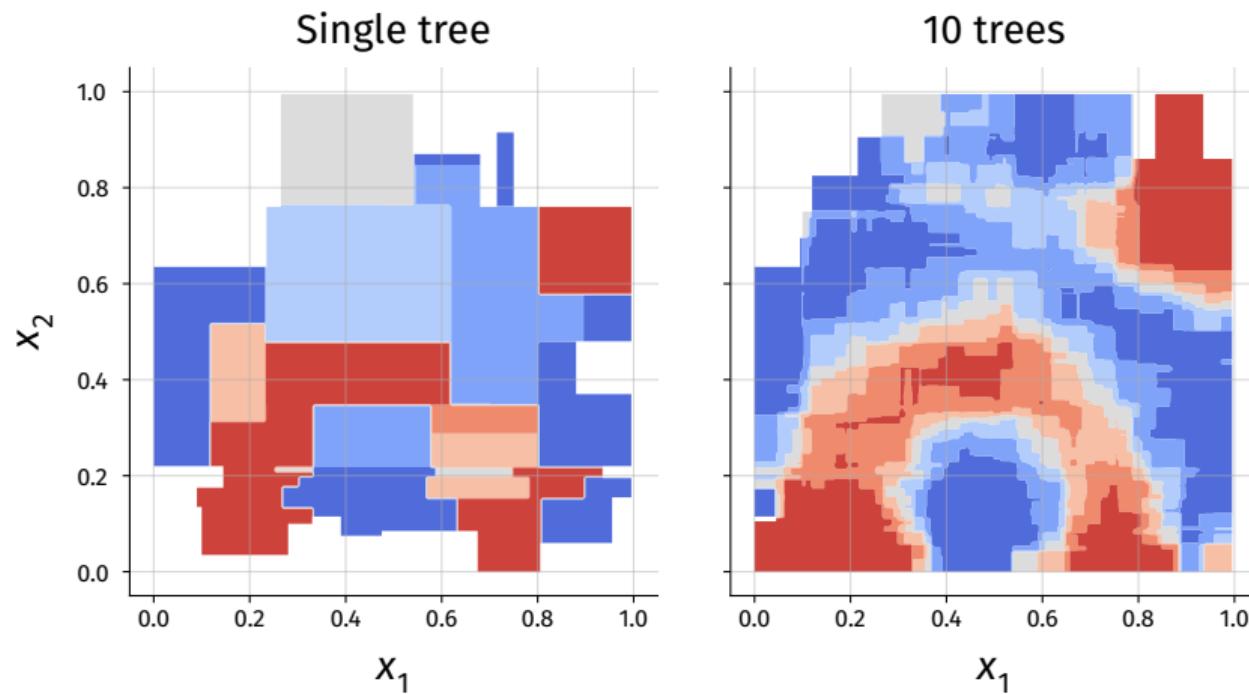
- Choose  $\delta \in [0, \frac{1}{2}]$
- Sample  $s$  in  $[a + \delta(b - a), b - \delta(b - a)]$
- $\delta = 0 \implies s \in [a, b]$  (uniform)
- $\delta = \frac{1}{2} \implies s = \frac{a+b}{2}$  (centered)



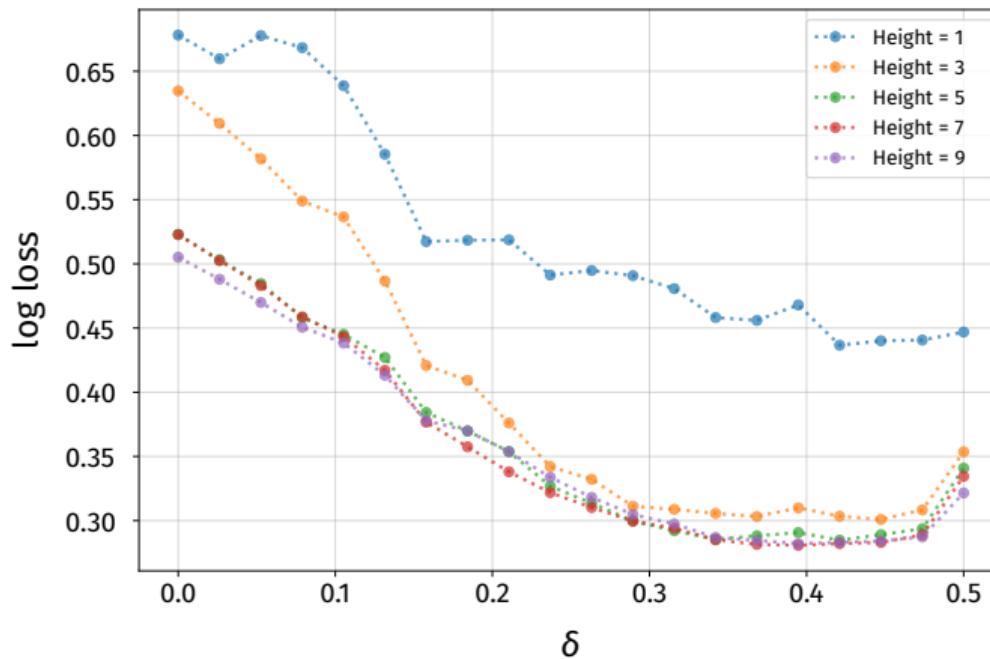
# Some examples



# Banana dataset with $\delta = 0.2$



# Impact of padding on performance



# Tree regularisation

- A decision tree overfits when its leaves contain too few samples
- There are many popular ways to regularise trees:
  1. Set a lower limit on the number of samples in each leaf
  2. Limit the maximum depth
  3. Discard irrelevant nodes after training (pruning)
- None of these are designed to take into account the streaming aspect of online decision trees

# Hierarchical smoothing

- Intuition: a leaf doesn't contain enough samples... but its ancestors might!
- Let  $G(x_t)$  be the nodes that go from the root to the leaf for a sample  $x_t$
- **Curtailment** [ZE01]: use the first node in  $G(x_t)$  with at least  $k$  samples
- Aggregated Mondrian trees [MGS19] use context weighting trees

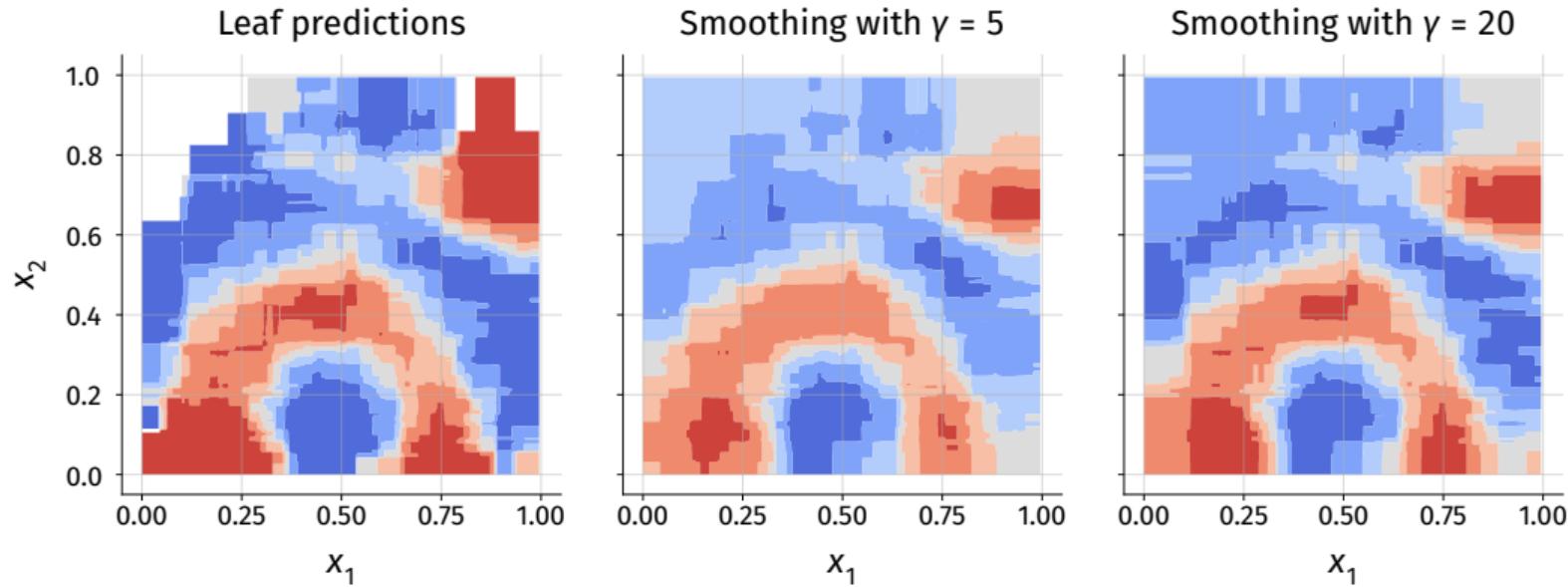
# A simple averaging scheme

- Idea: make each node in  $G(x_t)$  contribute to a weighted average
- Let
  - $k$  be the number of samples in a node
  - $d$  be the depth of a node
- Then, the contribution of each node is weighted by:

$$w = k \times (1 + \gamma)^d$$

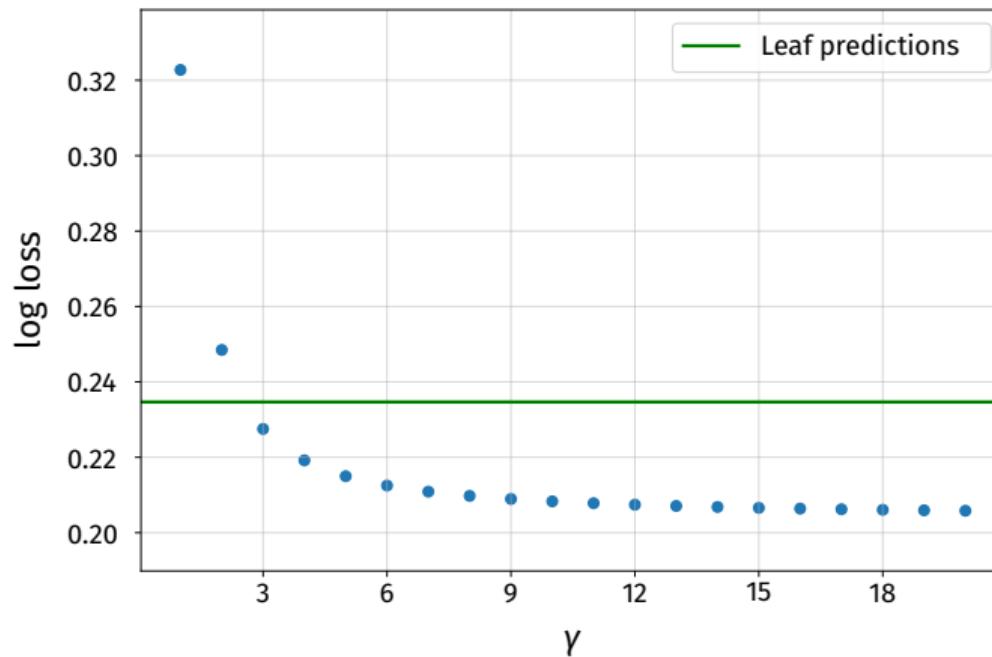
- The more samples a leaf contains, the more it matters
- The deeper a leaf is, the more it matters
- $\gamma \in \mathbb{R}$  controls the importance of both values
- I like to call this **path averaging**

# Averaging on the banana dataset



Notice what happens in the corners.

# Impact of $\gamma$ on predictive performance



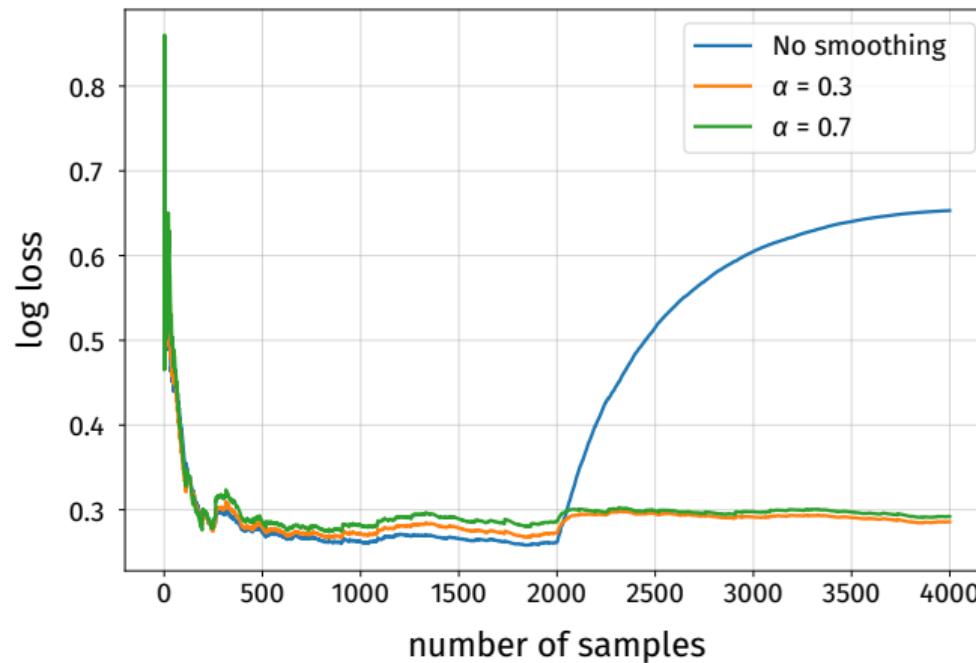
# Dealing with concept drift

- Each node contains a running average of the  $y$  values it has seen
- Instead, we can maintain an exponentially weighted moving average (EWMA):

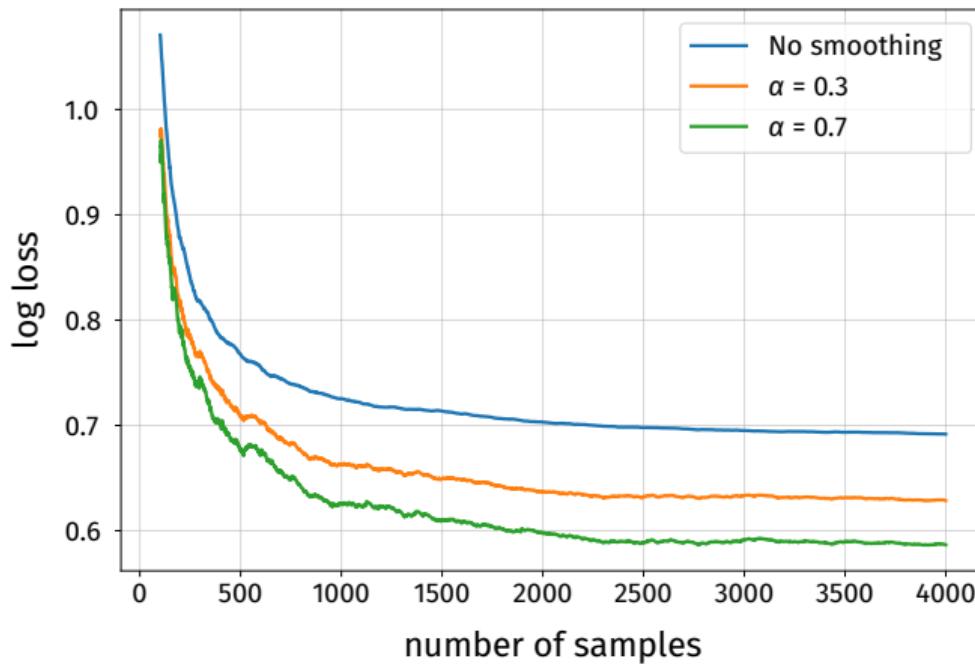
$$\bar{y}_t = \alpha y_t + (1 - \alpha) \bar{y}_{t-1}$$

- $\alpha$  determines the influence of the most recent values

# Hard drift: flip y values after 2000 samples



# Soft drift: slowly rotate samples around barycenter



# Feature selection

*Final paragraph from [MGS19] A limitation of AMF, however, is that it does not perform feature selection. It would be interesting to develop an online feature selection procedure that could indicate along which coordinates the splits should be sampled in Mondrian trees, and prove that such a procedure performs dimension reduction in some sense. This is a challenging question in the context of online learning which deserves future investigations.*

Online feature selection is a difficult problem!

# A solution?

1. Initially, we don't know the importance of each feature, so we pick them at random
2. After some time, we can measure the quality of each split within each tree
3. We can derive the feature importances from the splits each feature participates in
4. Every so often we can build a new tree by sampling feature relative to their importances
5. The selection probabilities should be conditioned on the features already chosen

This is still work in progress, but there is hope.

# Parameters recap

- $m$ : number of trees
- $h$ : height of each tree
- $\delta$ : the amount of padding
- $\gamma$ : determines how the path averaging works
- $\alpha$ : exponentially weighted moving average parameter

# Some useful Python libraries

- `scikit-garden` – Mondrian trees
- `onelearn` – Aggregated Mondrian trees
- `scikit-multiflow` – Hoeffding trees
- `scikit-learn` – General-purpose batch machine learning
- `creme` – General-purpose online machine learning

# Train/test benchmarks

	Moons	Noisy linear	Higgs	Higgs*
Batch log reg	.324	.244	.640	.677
Batch log reg with Fourier features	.193	.213	.698	.641
Batch random forest	.225	.210	.615	.639
NN with 2 layers	.171	.196	.653	.637
Online log reg	.334	.323	.662	.677
Mondrian forest	.349	.316	.692	.905
Aggregated Mondrian forest	.205	.199	.671	.649
Hoeffding forest	.330	.258	.664	.649
Padded trees (us)	.185	.193	.678	.644

# Streaming benchmarks

Work in progress!

*Slides are available at  
[maxhalford.github.io/slides/online-decision-trees.pdf](https://maxhalford.github.io/slides/online-decision-trees.pdf)*

*Feedback is more than welcome.*

*Stay safe!*

# References

-  Gérard Biau, Luc Devroye, and Gábor Lugosi.  
Consistency of random forests and other averaging classifiers.  
*Journal of Machine Learning Research*, 9(Sep):2015–2033, 2008.
-  Avrim Blum, Adam Kalai, and John Langford.  
Beating the hold-out: Bounds for k-fold and progressive cross-validation.  
In *Proceedings of the twelfth annual conference on Computational learning theory*, pages 203–208, 1999.
-  Leo Breiman.  
Bagging predictors.  
*Machine learning*, 24(2):123–140, 1996.

# References

-  Gérard Biau and Erwan Scornet.  
A random forest guided tour.  
*Test*, 25(2):197–227, 2016.
-  Tianqi Chen and Carlos Guestrin.  
Xgboost: A scalable tree boosting system.  
In *Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining*, pages 785–794, 2016.
-  Pedro Domingos and Geoff Hulten.  
Mining high-speed data streams.  
In *Proceedings of the sixth ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 71–80, 2000.

# References

-  João Gama, Indrė Žliobaitė, Albert Bifet, Mykola Pechenizkiy, and Abdelhamid Bouchachia.  
A survey on concept drift adaptation.  
*ACM computing surveys (CSUR)*, 46(4):1–37, 2014.
-  Jeremy Howard and Mike Bowles.  
The two most important algorithms in predictive modeling today.  
In *Strata Conference presentation*, February, volume 28, 2012.
-  Geoff Hulten, Laurie Spencer, and Pedro Domingos.  
Mining time-changing data streams.  
In *Proceedings of the seventh ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 97–106, 2001.

# References

-  Guolin Ke, Qi Meng, Thomas Finley, Taifeng Wang, Wei Chen, Weidong Ma, Qiwei Ye, and Tie-Yan Liu.  
Lightgbm: A highly efficient gradient boosting decision tree.  
In *Advances in neural information processing systems*, pages 3146–3154, 2017.
-  Balaji Lakshminarayanan, Daniel M Roy, and Yee Whye Teh.  
Mondrian forests: Efficient online random forests.  
In *Advances in neural information processing systems*, pages 3140–3148, 2014.
-  Jaouad Mourtada, Stéphane Gaïffas, and Erwan Scornet.  
Amf: Aggregated mondrian forests for online learning.  
*arXiv preprint arXiv:1906.10529*, 2019.

# References

-  Nikunj Chandrakant Oza and Stuart Russell.  
*Online ensemble learning.*  
University of California, Berkeley, 2001.
-  Liudmila Prokhorenkova, Gleb Gusev, Aleksandr Vorobev, Anna Veronika Dorogush, and Andrey Gulin.  
Catboost: unbiased boosting with categorical features.  
In *Advances in neural information processing systems*, pages 6638–6648, 2018.

# References

-  F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay.  
Scikit-learn: Machine learning in Python.  
*Journal of Machine Learning Research*, 12:2825–2830, 2011.
-  Daniel M Roy, Yee Whye Teh, et al.  
The mondrian process.  
In *NIPS*, pages 1377–1384, 2008.
-  Erwan Scornet.  
On the asymptotics of random forests.  
*Journal of Multivariate Analysis*, 146:72–83, 2016.

# References

-  Bianca Zadrozny and Charles Elkan.  
Obtaining calibrated probability estimates from decision trees and naive bayesian classifiers.  
In *Icml*, volume 1, pages 609–616. Citeseer, 2001.